

# Introduction to Hypothesis Testing

---

VT-DSPG 2025

Anbin Rhee

June 27, 2025

# Contents

---

1. What is a hypothesis?
2. The P-value
3. Type I error and Type II error
4. Hypothesis testing process

# Why Do We Need Hypothesis Testing?

---

As a data analyst, we often ask questions about data

- Does Ad Campaign A perform better than Ad Campaign B?
- Did the new teaching method improve student scores?
- Is the average height of students in our class the same as the national average?

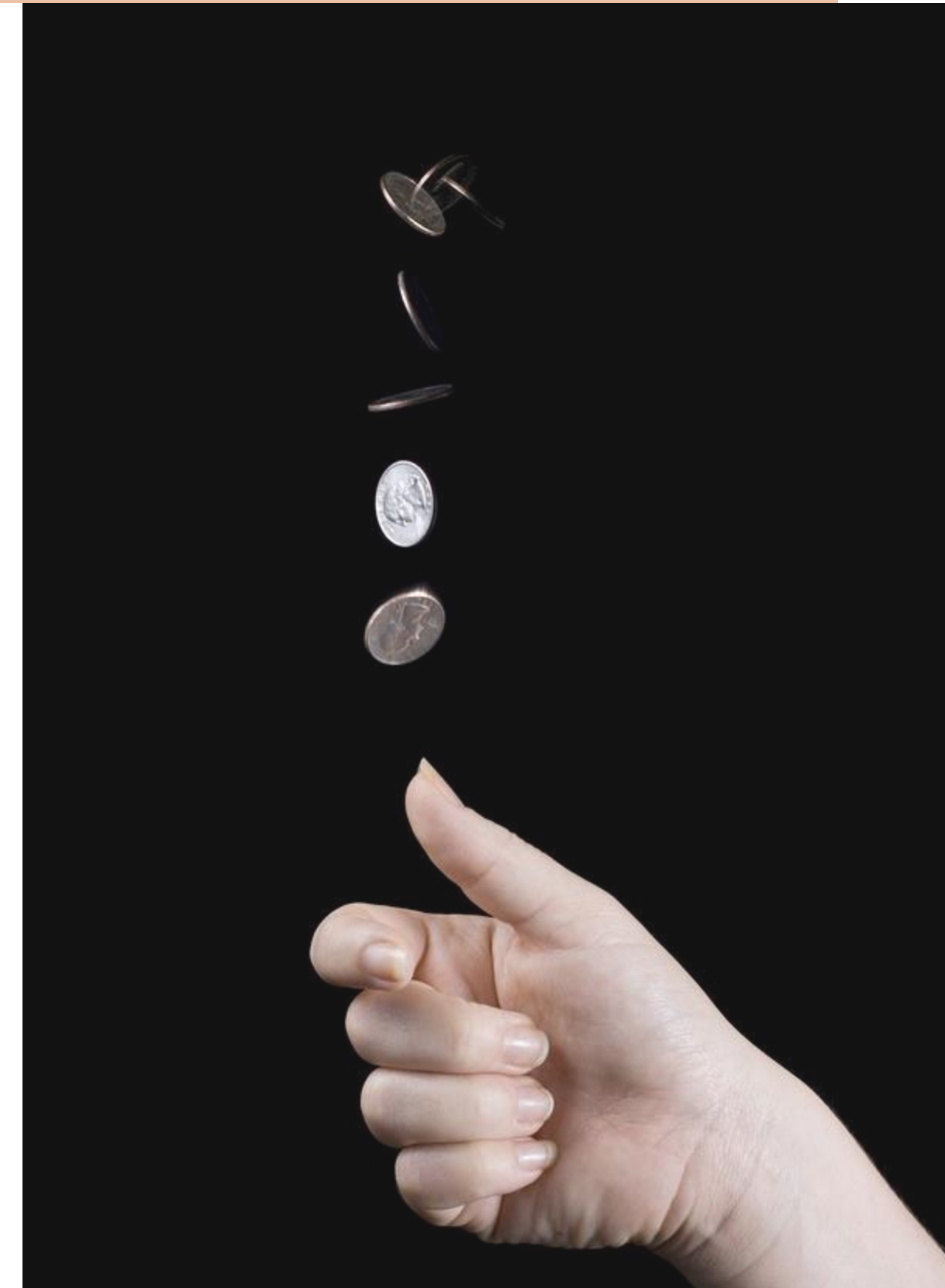
# Why Do We Need Hypothesis Testing?

Data can give us clues, but are these observations **real** or just due to **chance**?

Example: If you flip a coin 10 times and get 9 heads, is the coin really unfair, or did you just get lucky?

We need a formal rule so decisions are not based on gut feeling

Hypothesis testing is a **statistical tool** that helps us answer this question!



# What is a Hypothesis?

---

- A hypothesis is a testable statement or educated guess about a population or phenomenon.
- In hypothesis testing, we usually set up two competing hypotheses:
  - a. The status quo / no effect hypothesis
  - b. The alternative / effect hypothesis

# Null Hypothesis ( $H_0$ ) : The Status Quo

---

- The ‘default’ assumptions. It states there is no effect, no difference, or no relationship.
- Think of it like being “innocent until proven guilty” in a courtroom.  
We assume  $H_0$  is true unless we find strong evidence against it.

# Null Hypothesis ( $H_0$ ) : The Status Quo

---

- Examples:
  - $H_0$  : Ad Campaign A and Ad Campaign B have no difference in effectiveness
  - $H_0$  : The new teaching method has no effect on student scores
  - $H_0$  : The average height of students in our class is the same as the national average

# Alternative Hypothesis ( $H_1$ ) : Our Claim

---

- The hypothesis we are trying to find evidence for.
- It contradicts the null hypothesis.
- It states there is an **effect**, a **difference**, or a **relationship**.



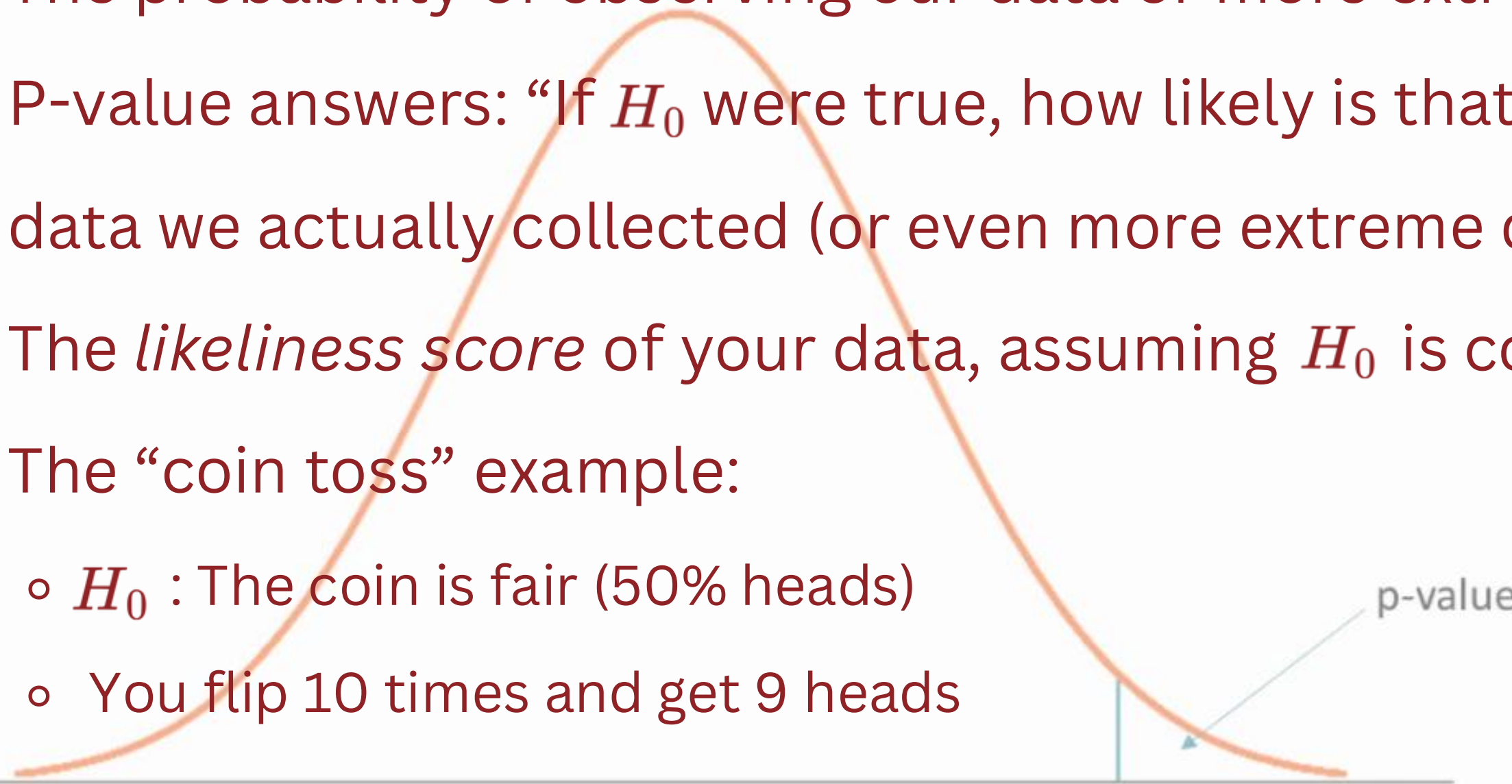
# Alternative Hypothesis ( $H_1$ ) : Our Claim

---

- Examples:
  - $H_1$  : Ad Campaign A is more effective than Ad Campaign B
  - $H_1$  : The new teaching method improves student scores
  - $H_1$  : The average height of students in our class is different from the national average

# P-value

- The probability of observing our data or more extreme data by chance.
- P-value answers: “If  $H_0$  were true, how likely is that we would observe the data we actually collected (or even more extreme data) purely by chance?”
- The *likeliness score* of your data, assuming  $H_0$  is correct
- The “coin toss” example:
  - $H_0$  : The coin is fair (50% heads)
  - You flip 10 times and get 9 heads



P-value: What is the probability of getting 9 or more heads in 10 flips if the coin is truly fair?

# Interpreting the P-value

---

- It is a metric to answer “Is our evidence strong enough?”
- Small p-value (e.g. 0.0001):
  - If  $H_0$  were true, seeing our data would be very rare
  - Conclusion: We have strong evidence against  $H_0$ . We reject the null hypothesis
- Large p-value (e.g. 0.8):
  - If  $H_0$  were true, seeing our data would be quite common
  - Conclusion: We fail to reject the null hypothesis

# The Significance Level ( $\alpha$ ):

---

- How 'small' is small enough for a p-value?
- We define a threshold called the **significance level** (  $\alpha$  )
- Common  $\alpha$  values: 0.05 (5%) or 0.01(1%)
- Decision Rule:
  - If p-value  $< \alpha$  : Reject  $H_0$  (The results is statistically significant)
  - If p-value  $\geq \alpha$  : Fail to reject  $H_0$  (The result is not statistically significant)

# No Guarantee in Statistics

- Even with statistical test, we are dealing with **probabilities**, not certainties.
- There is always a chance we make the wrong decision based on our sample data



# Type I Error: False Positive

---

- Definition: We reject the Null Hypothesis, but in reality,  $H_0$  was actually true.
- The Risk: The probability of committing a Type I Error is equal to our significance level,  $\alpha$ 
  - If  $\alpha = 0.05$ , there is a 5% chance of making a Type I error
- Example: Concluding a person is guilty when in reality the person is innocent





# Type II Error: False Negative

---

- Definition: We fail to reject the Null Hypothesis, but in reality,  $H_0$  was actually false.
- The Risk: The probability of committing a Type II Error is denoted as  $\beta$  which is related to statistical power
  - Statistical power =  $1 - \beta$
- Example: A person is truly guilty, but we found them not guilty due to insufficient evidence



# Trade-off between Type I and Type II Errors

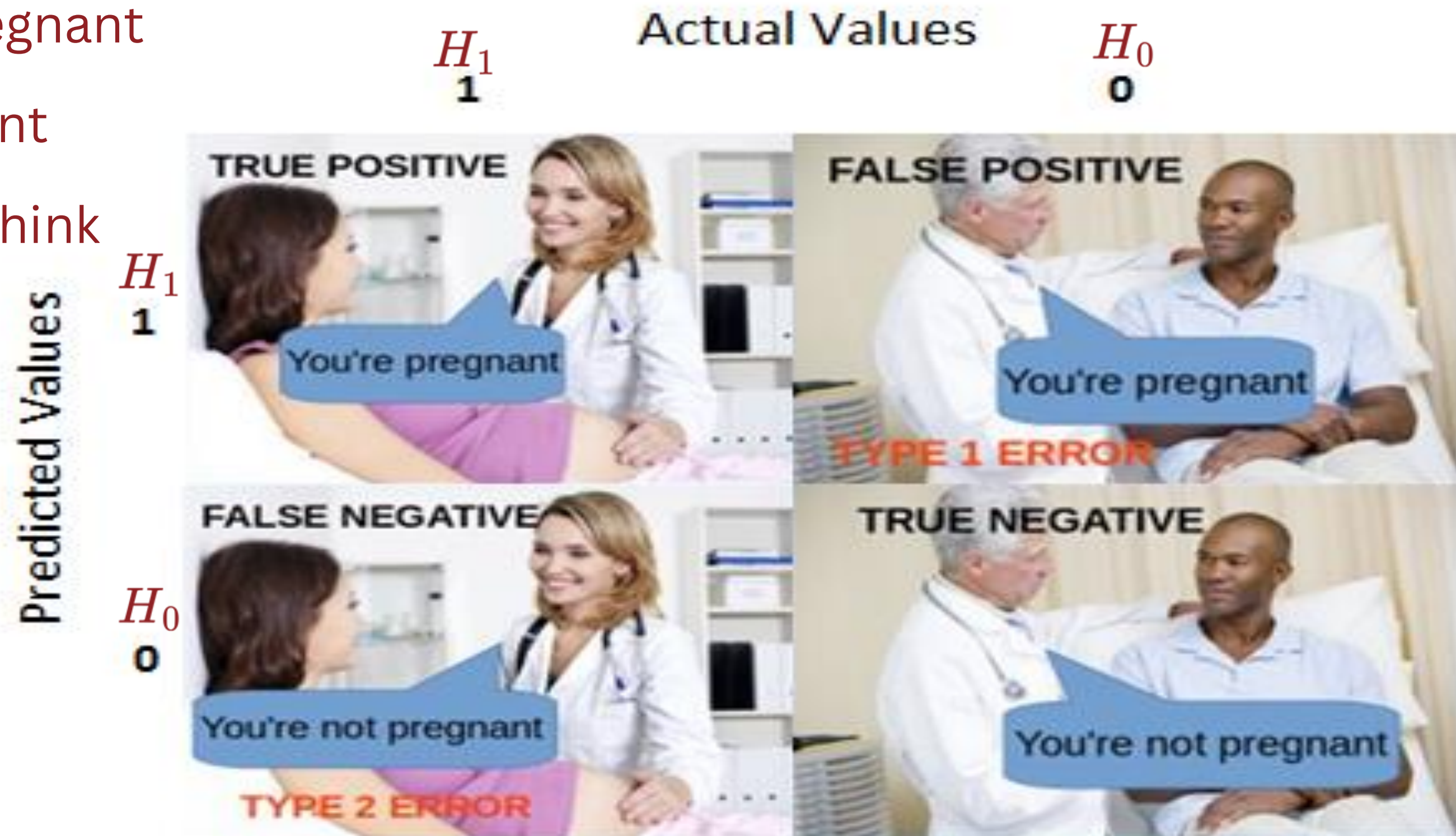
HYPOTHESIS TESTING OUTCOMES		REALITY	
		Null Hypothesis is True	Alternative Hypothesis is True
RESEARCH	Null Hypothesis is True	Accurate $1 - \alpha$ 	Type II Error $\beta$ 
	Alternative Hypothesis is True	Type I Error $\alpha$ 	Accurate $1 - \beta$ 

- Trade-off: Lowering  $\alpha$  reduces Type I error, but raises Type II error.
- The "best"  $\alpha$  depends on the consequences of each error in your specific situation.



# Trade-off between Type I and Type II Errors

- $H_0$ : Patient is not pregnant
- $H_1$ : Patient is pregnant
- Which error do you think is more costly or dangerous?



# The Hypothesis Testing Process

---

1. Formulate Your Question
2. State Your Hypotheses ( $H_0$  &  $H_1$ )
3. Collect Data and Perform Statistical Test
4. Calculate the p-value
5. Make a Decision : Compare p-value to  $\alpha$  (Reject  $H_0$  or not?)
6. Interpret Your Conclusion

# A Quick Example

---

## A Company develops a new fertilizer and wants to know if it increases crop yield

- Step 1: Does the new fertilizer increase crop yield?
- Step 2: Define hypotheses
  - $H_0$  : The new fertilizer has no effect on crop yield
  - $H_1$  : The new fertilizer increases crop yield
- Step 3: Imagine we run an experiment and perform a statistical test
- Step 4: Our analysis gives a p-value = 0.02 (Say our  $\alpha$  = 0.05)
- Step 5: Reject  $H_0$ !
- Step 6: We have statistically significant evidence to conclude that the new fertilizer increase crop yield. The company can be more confident about new fertilizer

# Why Hypothesis Testing Thinking Matters In Data Science

---

Suppose a company wants to predict which customers are likely to stop using their mobile app

- Modern data science often focuses on prediction, not inference
- Prediction-focused workflow may accurately predict who leave, but it tells us nothing about **why** they leave
- Many real-world questions still require hypothesis testing / inference
- Hypothesis testing provides a framework for rigorous reasoning



# Summary

---

- Hypothesis testing helps use make data-driven decision by assessing evidence
- Understand  $H_0$  and  $H_1$
- The p-value is the probability of observing our data by chance, if  $H_0$  is true
- We reject  $H_0$  when p-value is less than our threshold alpha
- Be aware of Type I error and Type II error
- Integrate hypothesis testing thinking beyond just algorithms to ensure rigor, interpretability, and trustworthiness in your research

# Next

---

- Commonly used statistical models
- When each model might be a good choice
- If there is something you'd like to learn in the next workshop, feel free to let me know!